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How simplifying urban driving cycles influence fuel consumption estimation?

Thamara Vieira da Rocha[a*], Bruno Jeanneret[b], Rochdi Trigui[b] and Ludovic Leclercq[a]

[a]*Université de Lyon, IFSTTAR, ENTPE, Laboratoire d'Ingénierie Circulation Transports (LICIT), France*
[b]*IFSTTAR, Laboratoire Transports et Environnement (LTE), France*

Abstract

Optimizing traffic management systems requires the development of dynamic traffic flow models capable of estimating environmental externalities. However, such models only produce simplified trajectories. Therefore they cannot be directly coupled with traditional emission models based on real trajectories, i.e. observed experimentally. The main objective of this research is to evaluate the impacts of using simplified instead of real trajectories as an input for a fuel consumption model, Vehlib library, developed at IFSTTAR/LTE.
Driving cycles were selected from 37 ARTEMIS urban driving cycles and processed. The resulting driving cycles were then simplified to make them correspond to the classical outputs of microscopic traffic flow models, i.e. piecewise linear speed profiles. The simplification method used is based on a genetic algorithm with a given number of break points. Reducing the number of such points leads to several levels of simplification. The fuel consumption is then estimated for each simplified driving cycle and its original.
A deeper analysis is finally provided to evaluate the error between fuel consumption estimations for original and simplified sub-cycles. The first results show average error equal to -1.27% for simplified sub-cycles with average RMSE equals to 0.90km/h. According to the level of simplification, the average error is equal to -0.13% at fine level, -0.77% at intermediary level and -2.42% at coarse level. A complementary analysis is also provided studying individually several sub-cycles to figure out which kinds of simplification have the main influence on fuel consumption.

Keywords: Fuel consumption estimation; Vehlib library; Driving cyles; Trajectories simplification;Genetic algorithm.

* Corresponding author. Tel.: +33-472-047-229 ; fax: +33-472-047-712 .
E-mail address: Thamara.VIEIRADAROCHA@entpe.fr

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1. Introduction

Despite the reduction of individual vehicles consumption rate with the introduction of new technologies, the increase of vehicles numbers leads to a global increase of total fuel consumption and their relating greenhouse gas emissions. This contribution should be accurately estimated to determinate how advanced traffic management systems may help to reduce it.

A new field of research tries to connect dynamic traffic models with emission models to improve fuel consumption estimation. Zegeye et al. (2010) propose a new macroscopic emission and fuel consumption model denoted the VT-macro model. This model results from the coupling between macroscopic traffic flow model METANET and microscopic emission and fuel consumption model VT-micro. Rakha et al. (2011) present the INTEGRATION microscopic traffic simulation framework for modeling eco-routing strategies and the related savings in fuel consumption. Yu (1998) presents the development of the ONROAD vehicle emission model for estimating CO and HC emissions. On the contrary to INTEGRATION model based on vehicle modal activities, this model establishes a relationship between on-road emission data and vehicle instantaneous speed profiles. This model is proposed as ideal for use in traffic simulation and optimization analysis.

The point here is that none of the traffic flow models produces real trajectories but only simplified ones. Their outputs are simplified trajectories based on simplistic kinematic rules because they mainly focus on vehicle interactions. Consequently one major question is the relevance of these simplified trajectories as an input of an emission model. Few studies have paid attention to this crucial point and this work aims to contribute to fulfilling this shortage.

To start, we chose real driving cycles representing urban conditions. These driving cycles come from the ARTEMIS database (ARTEMIS project's report, 2007). The first step consists in selecting and processing these cycles to obtain a reference set of sub-cycles. A sub-cycle provides the evolution of speed with respect to time between two stops longer than six seconds. In the next step a genetic algorithm is applied on these sub-cycles to obtain the piecewise linear approximations, i.e. a speed profiles with piecewise constant acceleration, with a given number of action points. An action point is defined as a point where a change in acceleration is observed, i.e. a point where the jerk is not null (acceleration to deceleration or vice-versa). Reducing the number of such points leads to several levels of simplification. Simplifications remove the noise observed in real sub-cycles and make these sub-cycles closer to those produced by traffic flow models. However, different acceleration values in a same global acceleration phase are allowed. The resulting simplified sub-cycles do not then strictly correspond to what would be observed as an output of a traffic model. However, this gives a first prospective look of the impacts on fuel consumption when kinematic simplifications are made. Note that we chose to simplify real driving cycles rather than making simulated driving cycles look real because there is, to our knowledge, no existing simple methodology for this reverse transformation.

Fuel consumption for original and simplified sub-cycles is then computed using the Vehlib library (TRIGUI et al., 2004; VINOT et al., 2004). The fuel consumption differences are first studied for the whole sub-cycle set, for several levels of simplification. Then, several sub-cycles are individually studied to figure out which kinds of simplification have the main influence on the fuel consumption.

This paper is organized as follows. Section 2 deals with: the data processing, the simplification method and the fuel consumption estimation. Section 3 describes the results and their analysis. The conclusion is finally presented in section 4.

2. Materials and Methods

2.1. Data processing

37 urban driving cycles were selected from ARTEMIS real-world driving cycles for passenger cars (ARTEMIS project report, 2007). They are divided in 249 sub-cycles by identifying stops that last at least 6 seconds. A cluster analysis has been performed to define 25 homogeneous groups of sub-cycles in terms of traffic characteristics in order to reduce the database size. The considered main traffic characteristics for this clustering analysis are: travel time, distance traveled, stop duration, maximum and average speed, and maximum acceleration and deceleration. For each group of sub-cycles the most different sub-cycles are selected defining a set of 39 sub-cycles that provides a statistically representative description of the possible encountered traffic situations. The sub-cycles provide the evolution of speed with respect to time, with a time step equal to 1s.

2.2. Simplification method

A genetic algorithm is used to transform one sub-cycle into a piecewise linear function with a fixed number of action points. Reducing this number provides several simplification levels. The simplification level is defined by the ratio between the number of considered AP and the total number of time points in the original sub-cycles. Note that original sub-cycles are defined with a time step of one second. Thus, the total number of time point is equal to the duration of the sub-cycle. The genetic algorithm tries to minimize the RMSE between the original and the simplified sub-cycle.

The algorithm is defined by the parameters described hereafter. The population size is adapted to the considered number of actions points (AP). A sample of this population is defined by the list of the positions in time of the action points. During the reproduction step two crossovers are considered. They are defined by the number of AP before the crossover positions. The minimal considered number for action points is six. The positions of crossovers depend on the number of AP, see Table 1.

Table 1. Population size and crossover positions with respect to the number of AP.

Parameter	**AP ≥30**	**10 ≤ AP < 30**	**10 < AP ≤ 6**
Population size	12	8	4
Crossover position 1	4	3	2
Crossover position 2	8	6	4

Two kinds of mutations are possible: minor mutation corresponds to the incrementation of AP position of ±1. Major mutation corresponds to a random change of an action point position. The probability of minor mutation is 0.09% and 0.005% for major mutation. An elitist selecting method is applied, i.e. only the best samples are kept to define the new population after the reproduction and the mutation steps. The algorithm stops either when a maximum number of iterations is reached (N=1500) or when the RMSE has been stabilized for at least 150 iterations.

2.3. VEHLIB library – Fuel consumption estimation

The VEHLIB library was developed by IFSTTAR/LTE with the objective of simulating the vehicles dynamic performances and energy consumption for conventional, electric and hybrid vehicles. It is based on a cybernetic representation of the vehicle i.e., the vehicle is viewed as a set of sub-systems. The vehicle is thus decomposed into different units that are separately modeled. The interactions between units respect a strict forward looking approach (TRIGUI et al., 2004; VINOT et al., 2004). VEHLIB models are validated by measures on engine test stand and on chassis dyno.

In this study, fuel consumption for original and simplified sub-cycles was computed using a simplified backward approach derived from VEHLIB library. While VEHLIB simulates many types of passenger cars, we only consider one vehicle in this work, i.e. a conventional diesel Clio II equipped with a 1.5L DCI engine.

3. Data analysis

The study of the impacts of the simplifications is decomposed in two parts. First, the whole set of simplified sub-cycles is analyzed to demonstrate how simplification influences fuel consumption estimation at a macro scale, i.e. by considering the total fuel consumption for the entire sub-cycle. Then, the study is completed at a micro scale by considering some specific sub-cycles to determine which kinds of simplification have the main influence on the fuel consumption. At this level, we focus on the evolution of the fuel consumption with respect to time.

3.1. Macro analysis

The average duration for the 39 original driving sub-cycles is equal to 83s. It varies from 20 to 193s. The average speed is 21.2km/h and the maximum one is 73.5km/h. After simplifying, 1367 simplified sub-cycles are obtained with the genetic algorithm and different levels for the number of action points. The following parameters are calculated for each sub-cycle:

- The standard relative error on the fuel consumption estimation [FC error] (%): it corresponds to the relative difference between fuel consumption on the original and the simplified sub-cycles.
- The reduction in the number of action points [AP reduction] (%): it corresponds to the relative positive difference between the action points' number in the simplified sub-cycle and the total time points in the original one.
- The RMSE: the root mean squared error between both sub-cycles. This error defined the root mean squared difference in speed every second on the speed profile.

The genetic algorithm does not always provide the optimal profile for a given number of points. For this reason, the results are filtered by RMSE according to the following procedures. The simplified sub-cycles related to the same original sub-cycle are gathered and sorted in ascending order with respect to the number of action points. The simplified driving cycles from a same group but with higher RMSE than its predecessor are disregarded. As result, only 812 simplified sub-cycles are studied.

The AP reduction varies between 24.1% and 96.9%. Low levels of AP are not considered because the resulting simplified sub-cycles are not enough simplified, i.e. a high frequency noise is still observed for acceleration. Three levels of simplification are then distinguished by analyzing the sub-cycles profiles and the RMSE with respect to the AP reduction (Fig. 1a). These levels are: fine, intermediary and coarse. Moreover, Fig. 1b presents the FC error with respect to the AP reduction. The mean curve of this function and the boundaries including 80% of data are also provided.

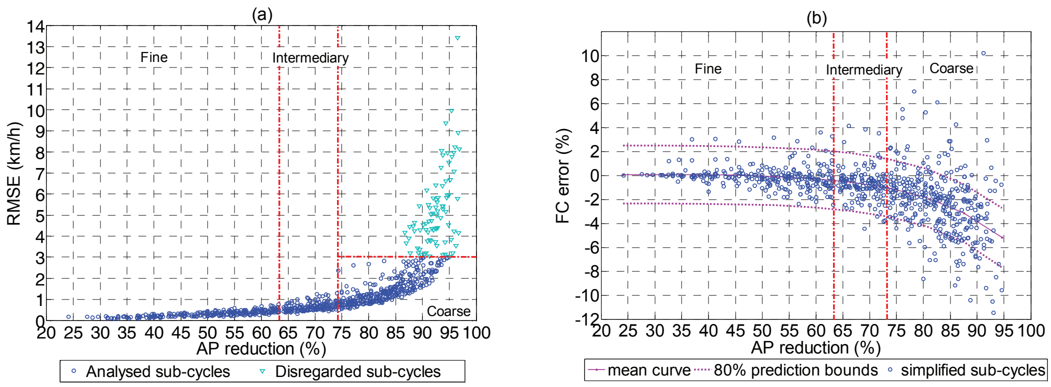

Fig. 1. (a) Evolution of the RMSE with respect to the AP reduction. (b) Evolution of the FC error with respect to the AP reduction.

The fine level corresponds to RMSE values lower than 0.75km/h. It corresponds to AP reduction lower than 63.3%. The average RMSE is equal to 0.33km/h (the RMSE increases between 0.09 and 0.75km/h). At this level, only the high frequency but low amplitude noise is eliminated. The intermediary level is bounded by RMSE values lower than 2.37km/h. It corresponds to AP reduction between 63.3% and 74.3%. The average RMSE is equal to 0.66km/h (the RMSE increases between 0.33 and 2.37km/h). The variations of accelerations are more smoothed than at the fine level. The coarse level corresponds to AP reduction higher than 74.3% and RMSE lower than 3.0km/h. The average RMSE is equal to 1.46km/h (the RMSE increases between 0.50 and 3.0km/h). The simplified cycles have longer phases of constant acceleration than both previous levels. 31.2% of data corresponds to the fine level, 19.3% to the intermediary level and 39.3% to the coarse level.

From the data set, the increase of AP reduction results in an exponential increase of the RMSE (the average RMSE is equal to 0.90km/h). High values of RMSE (the RMSE higher than 3km/h) lead to simplified sub-cycles that are far away from the originals. These kinds of simplification are not relevant for our study and the corresponding sub-cycles have been disregarded. It corresponds to 10.2% of simplified sub-cycles.

As the AP reduction increases, the FC error also tends to increase negatively. The average error is equal to -1.27% for sub-cycles set. According to the simplification level the average FC error is equal to -0.13% at fine level (the FC errors varies between -2.47% and 3.57%), -0.77% at intermediary level (the FC errors varies between -4.47% and 4.13%) and -2.42% at coarse level (the FC errors varies between -11.46% and 10.20%).

The main result here is that FC error is not very sensitive to the AP reduction. It appears that we can significantly simplify the real sub-cycle without introducing crippling bias in fuel consumption estimation. This first result should be confirmed with a refine analysis.

3.2. Micro analysis

We now study some particular sub-cycles and investigate the evolution of fuel consumption with respect to time. To emphasize the difference in fuel consumption, we will focus on the cumulative consumption with respect to time for simplified and original patterns. When these two curves diverge, it means that the kinematic simplifications imply a significant error. This error may (i) never be compensated and then play a significant part of the total FC error, (ii) be quickly compensated in the same driving phase (acceleration, deceleration or cruising) or (iii) be compensated but latter in sub-cycle. We will mainly focus on error types (i) and (ii) because the third one result from hazard and cannot drive any simplification guidance.

The cumulative consumption curves are compared with the respective speed profiles to determine the kinds of simplification that most influence the fuel consumption. Only three sub-cycles (ID = 39, 32, 25) are selected for this micro analysis (but several level of simplifications are investigated). These sub-cycles highlight different cases:

- Sub-cycle 39 has simplified sub-cycles with FC error always inside the error bounds for all sub-cycles. The FC error is very low for low values of AP reduction. It tends to increase with the increase of the AP reduction, especially from coarse level (AP reduction equal to 89.6%). This sub-cycle lasts 173s and has average speed equal to 37.3km/h.
- Sub-cycle 32 corresponds to a case where FC errors are high even for low AP reduction values. The simplified sub-cycles have high FC error until AP reduction equal to 80.4%. Sub-cycle 32 is a short sub-cycle that lasts 46s and has low average speed equal to 5.5km/h.
- Sub-cycle 25 was studied to best identify the kinds of simplification in coarse level (high RMSE) that lead to high FC error (fuel consumption underestimated). The simplified sub-cycles start with low FC error (-0.33%) and then increase discontinuously with the increase of the AP reduction. This sub-cycle lasts 96s and has average speed equal to 39.9km/h.

Fig. 2 presents the evolution of the FC error and the RMSE with respect to the AP reduction for these sub-cycles. The mean FC error values and bound encompassing 80% of the studied sub-cycles are also represented in this figure.

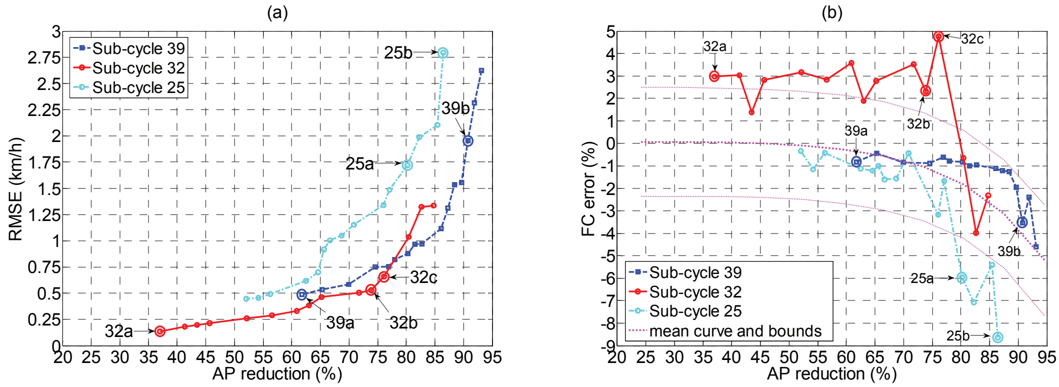

Fig. 2. Evolution of (a) the FC error and (b) the RMSE with respect to the AP reduction.

The Fig. 3 presents the cumulative consumption curve and the speed profile for the three selected sub-cycles and the most representative levels of simplification see Fig. 2.

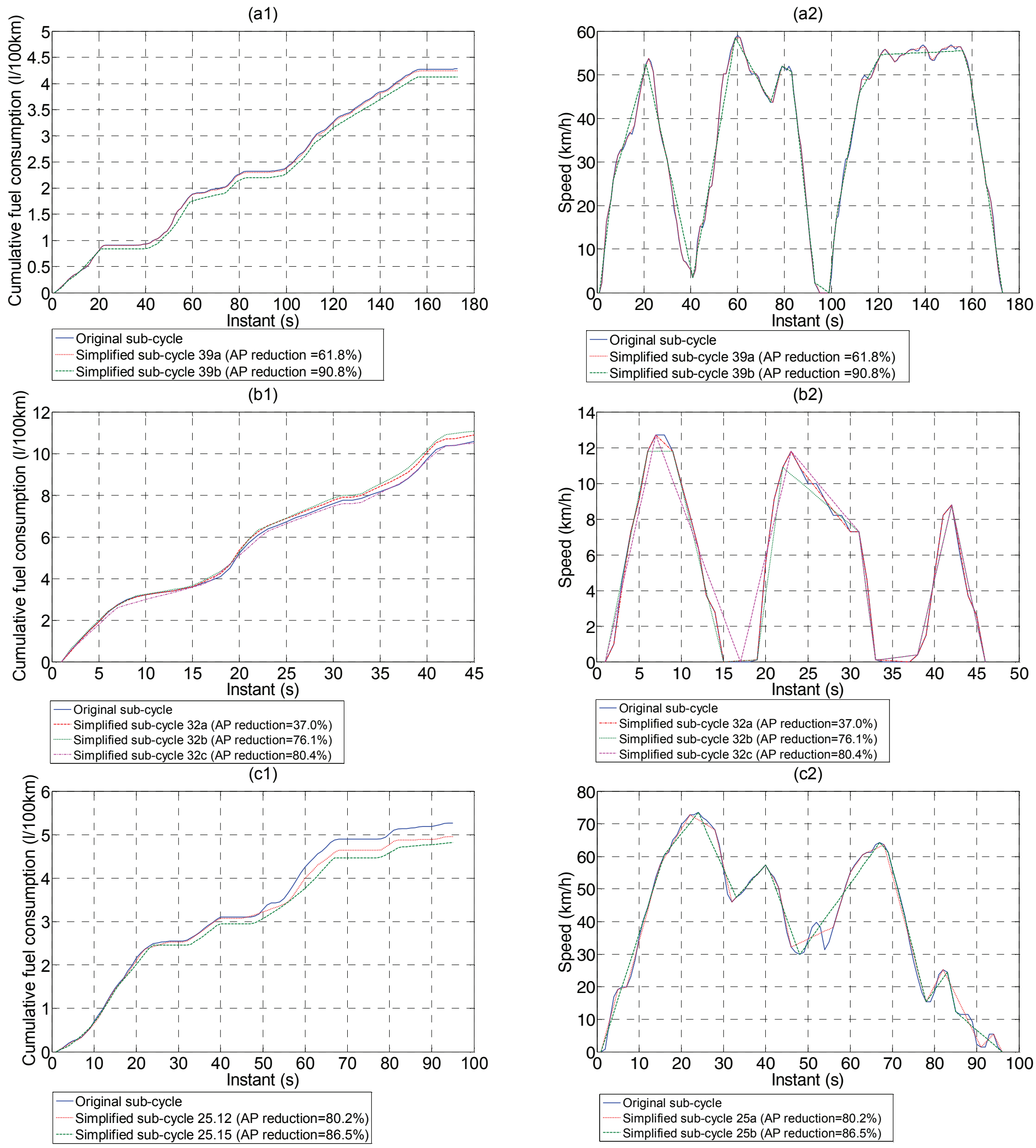

Fig. 3. (a) Sub-cycle 39, (b) sub-cycle 32, (c) sub-cycle 25. (1) Cumulative fuel consumption with respect to time, (2) Speed profile.

The accelerations phases are responsible for higher fuel consumption than the deceleration phases. An significant difference is seen when the deceleration phase occurs at high speed (e.g. sub-cycle 39 and 25) or at low speeds (e.g. sub-cycle 32). In the first case, the Electronic Control Unit of the engine pilots an injection cut-off and the fuel consumption is equal to zero, i.e. the cumulative curve remains constant. In the second case, the fuel consumption continues to increases with lower values than in acceleration phase. Additionally, the phases with zero speeds also contribute to fuel consumption.

We now deal with the impacts of different levels of simplification. The levels are denoted with lower use letter after the sub-cycle ID, see Fig. 3. Sub-cycle 39a corresponds to a fine simplification with a cumulative consumption curve close to the original. The resulting FC error is low (-0.82%). For sub-cycle 39b, the maximal speed is not reached at time 22s in the simplified sub-cycle. The cumulative fuel consumption at the end of the acceleration phase is then underestimated. This corresponds to a type (i) error, i.e. the contribution of this error on the total error is equal to 22.8%. Moreover, the simplification between 122 and 156s replaces the original speed profile by a phase on constant and low acceleration. The initial speed is 54.6km/h and increases until 55.5km/h. This simplification has low impact on fuel consumption.

The different levels of simplification for sub-cycle 32 show that kinematic errors during phase with zero speed induces significant errors on fuel consumption, see time 34 to 37s and time 15 to 18s. As result, these simplifications overestimate the fuel consumption for sub-cycles 32a and 32b. The simplifications of this first phase are the same for sub-cycles 32a and 32b. However, as this simplification does not cause a local error in sub-cycle 32b, we can conclude that it is corrected by another simplification. After the end of this phase in zero speed (instant equal to 18s), the simplifications cause local errors that cumulate until the FC error of sub-cycle 32b. Additionally, the reduction of the maximal speed at instant equal to 6s does not cause an error on fuel consumption estimation. As the maximal speed reached is low (11.8km/h), the fuel consumption continues to increase close to the original. In sub-cycle 32c, the combination of the simplifications (including the simplification of the second phase on zero speed) results in a low FC error (-0.66%). The simplification of the discontinuous deceleration phase between 23 and 31s in sub-cycles 32a and 32c does not impact the cumulative consumption curve.

In sub-cycle 25a, the deceleration phase that starts at instant 40s has same maximal speed that the original but reaches higher minimum speed. This last point is anticipated in time (instant equal to 46s instead of 48s) and the fuel consumption for the next acceleration phase increases earlier. During this deceleration phase the consumption curve remains close to the original because maximal speeds are the same.

Additionally, the simplified sub-cycles 25a and 25b have error coming from the simplification of the oscillation between 48 and 54s in original sub-cycle. The oscillation corresponds to an acceleration followed by a deceleration phase. In sub-cycle 25b, it is replaced by a constant acceleration phase between 46 and 56s. In sub-cycle 25b, it is also replaced by a constant acceleration phase but longer, from time 48s to 67s. Both simplifications contribute to the FC error, higher in sub-cycle 25b than in sub-cycle 25a. Reducing the maximal speed at 67s in sub-cycle 25b also has great impact on FC error. The simplifications made from the instant 68s have low impact on fuel consumption in both simplifications.

4. Conclusion

This paper tries to characterize how simplifications on vehicle speed profiles influence the fuel consumption. Simplifications from real driving cycles are obtained through a genetic algorithm that progressively reduces the number of possible action points. The fuel consumption is estimated using VEHLIB library.

First, the impacts of simplifications have been evaluated at a macro level. All sub-cycles have been simplified with different values of the AP reduction. Results show that an increase in AP reduction negatively increases the FC errors especially for the coarse level, i.e. the simplification tends to underestimate the fuel consumption. The FC error is equal to -1.27%. It is equal to -0.13% for the fine level (AP reduction <63.3%), -0.77% for the intermediary level (AP reduction between 63.3% and 74.3%) and -2.42% for the coarse level (AP reduction >74.3% and RMSE <3.0km/h).

A complementary analysis has determined which kinds of simplification have the main influence on the fuel consumption. This is achieved by studying the evolution of fuel consumption over time (cumulative fuel consumption with respect to time). The time when the cumulative consumption curve of the simplified sub-cycle moves away from the original represents a local error on fuel consumption estimation. The localization of these specific errors can then be investigated on the speed profile.

This study shows that, by reducing the number of action from the original cycle, the genetic algorithm first eliminates high frequency but lowers amplitude noise. Indeed variations in acceleration are smoothed. The acceleration phases are then reproduced with only a few successive values of constant acceleration. The deceleration phases are treated the same way. Such kinds of simplifications seem to have no or a relatively low impact on fuel consumption.

Going on in reducing the number of action points eliminates noise with low frequency and/or higher amplitude. From here, the position of the action point and the speed value seems more important. However, some action points are more important for fuel consumption estimation than others. These actions points correspond to signal changes in acceleration and more precisely the points when the speed reaches its maximum value before a deceleration phase. Introducing errors on the maximum (respectively minimum) speed value at the end of an acceleration (respectively deceleration) phase leads to significant errors on fuel consumption. Furthermore, higher the maximum speed higher the fuel consumption is.

Additionally, an acceleration phase with one or more significant change on acceleration value can be replaced by a phase with different successive values of acceleration. If this kind of speed profile is replaced by another with only one acceleration value, the FC error tends to be higher. The deceleration phases are treated the same way.

The minimum speed at the end of a deceleration phase is less important than the maximum speed at the end of an acceleration phase. Moreover, vehicle standstill can highly influence the fuel consumption even at fine level. This kind of simplification overestimates the fuel consumption.

The conclusions taken from this work try to give a first answer to the impacts of using simplified instead of real trajectories as an input for a fuel consumption model. The major observation is that simplified driving cycles can still maintain good fuel consumption estimation.

A deeper study must continue to identify more precisely the best kinds of simplifications that should be applied according to the speed profile. This can contribute to better estimate speed profiles considering fuel consumption. Moreover, further research is required to better understand the impacts of coupling traffic and fuel consumption models on fuel consumption estimation.

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